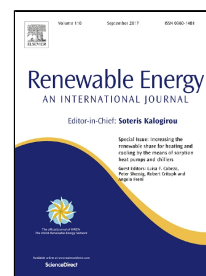


# Accepted Manuscript

## Solar Power Potential of Tanzania: Identifying CSP and PV Hot Spots through a GIS Multicriteria Decision Making Analysis

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# **Solar Power Potential of Tanzania: Identifying CSP and PV Hot Spots through a GIS Multicriteria Decision Making Analysis**

## **Abstract**

More than one billion people are still living without access to electricity today. More than half of them are living in Sub-Saharan Africa. There is a noticeable shortage of energy related information in Africa, especially for renewable energies. Due to lacking studies and researches on integrating renewable energy technologies, the Tanzanian official generation expansion plan till 2035 showed high dependency on fossil fuel and a negligible role of renewables other than large hydropower.

This study investigates the spatial suitability for large-scale solar power installations in Tanzania through using Geographic Information System (GIS) analysis combined with Multicriteria Decision Making (MCDM) technique. The study identifies six exclusion criteria to mask unsuitable areas. Then the Analytic Hierarchy Process (AHP) method is used to determine the weights of seven identified ranking criteria. A final technology-specific suitability map categorizes all the non-excluded areas into most suitable, suitable, moderately suitable, and least suitable areas. The study also suggests four hot spots (i.e. specific recommended locations) for Concentrated Solar Power (CSP) installations and four hot spots for Photovoltaics (PV) installations.

The combined GIS-MCDM methodology presented in this paper is applicable to similar investigations in other regions and for evaluating the spatial suitability of other renewable energy technologies.

## **Keywords**

Solar power  
GIS  
Multicriteria decision making  
Location suitability  
Tanzania

## **1. Introduction**

There are 1.2 billion people who do not have access to electricity today, the African continent has the lowest electrification rate and 99.8% of the African population without electricity is concentrated in Sub-Saharan Africa (SSA) [1]. More than 600 million people in SSA are still in the dark after nightfall, hospitals cannot refrigerate vaccine, school children often cannot read after sunset, businesses cannot grow, and industries are idled hindering economic growth. Only 30% of Tanzanians have access to electricity [1], hence increasing the electrification level is one of the main priorities for the Tanzanian government. This goal is highly supported by the UN Sustainable Energy for All global initiative, and there is a growing consensus among international development partners to tackle the electricity crisis in SSA. According to the Tanzanian official generation expansion plan, in 2025 the fossil fuel fired power plants will represent 75% of the total installed capacity compared to 20% from hydropower plants and 5% from other renewables [2], after 2025 the power mix is expected to still be dominated by fossil fuel based technologies (especially the newly introduced coal-fired power plants which are expected to represent more the 40% of the installed capacity in 2035) and large hydropower [3]. It is obvious that, regardless their significant potential, wind and solar resources are mostly ignored.

A study by the Joint Research Centre (JRC) of the European Commission [4] concluded that “compared to the rest of the world, there is a general shortage of energy related information in Africa (especially for renewable energy) leading to large energy planning uncertainties due to such scattered validated information”. The current Tanzanian power system strategy (updated in 2012) only leaves room for a very limited role of renewable energies other than large hydropower, due to the lack of relevant studies to support power planning methods which can promote the integration of renewable energy technologies [3]. The Tanzanian government investment plan submitted to the World Bank in 2014 [3] stressed that Tanzanian power system planners are in strong need for high-quality energy research to allow them making informed decisions. It is clear that conducting energy-related research especially on renewables will bridge a demanding research gap and will add value to the Tanzanian power system planning sector in specific.

Since 2011, the Tanzanian government is realizing the substantial fuel expenses associated with the introduction of an emergency power generation plan (based on diesel fuel) after the 2010 droughts that reduced the generation from hydropower drastically [3]. On the other hand, Tanzania as a member of the international community started to realize the environmental concerns resulting from burning fossil fuels for electricity generation. It is also noticeable that the current development policies of many donors and development organizations focus on the deployment of renewable energy resources. Consequently, the Tanzanian government declared that “it is eager to take a more proactive and inclusive role to promote viable renewables options, rather than the current practice of only waiting for unsolicited renewables project proposals by interested parties” [3].

Most of the solar power projects in SSA (including Tanzania) are photovoltaic installations applied on decentralized micro- or mini-scale. An American study supported by the Knowledge for Change Program of the World Bank [5] concluded that “although decentralized renewables will likely play a role in rural electrification, they will be the lowest cost option for a minority of households in Africa even when likely cost reductions over the next 20 years are considered”. The study [5] showed that although decentralized renewables are competitive mostly in remote and rural areas, a grid connected supply is favoured in denser areas where the majority of industries, businesses, and households are located. It is clear that regardless of the increasingly introduced decentralized renewable-based installations (which are mostly in kW scale), the power mix of SSA countries would not be considerably less dependent on fossil fuel without introducing and fostering the renewables on the centralized power generation scale as it expands.

Identifying and prioritizing suitable areas for building large-scale solar power plants is a complex problem. In contrast with the simplistic view, identifying appropriate geographical areas for solar power installation is not only linked with the amount of received solar radiation, but there are many other technical, economic, environmental, and social factors that should be considered like: alternative land uses, topographical characteristics of the land, conserving protected areas, potential environmental impacts, water availability, potential urban expansion, proximity to demand centres, roads proximity, and potential for grid connectivity.

To tackle such challenging problem of prioritizing suitable areas according to multiple diverse factors, this study used a Geographic Information System (GIS)-based Multicriteria Decision Making (MCDM) approach to develop a technology-specific suitability index for the entire territories of the United Republic of Tanzania to have large-scale solar power installations. Among MCDM techniques, the Analytic Hierarchy Process (AHP) method has been used to determine the weights of the multi-level

hierarchical structure (i.e. decision clusters and ranking criteria) through performing pairwise comparisons.

MCDM methods handle the process of making decisions where multiple objectives are considered (e.g. for determining a favourable location for a solar plant, solar radiation, proximity to road, proximity to utility grid ...etc. are considered desirable objectives). Hence the decision should be made taking into consideration multiple criteria. The applications of MCDM spans wide research areas, including integrated manufacturing systems [6], technology investment's evaluation [7], water resources management [8], irrigation system's evaluation [9], and energy planning [10-18] to name a few. When addressing a sustainable energy decision making problem (e.g. determining the most suitable areas for building a solar plant) there are many criteria that need to be taken into account, hence it is important to determine each criterion's relative impact on the final decision to be made. Consequently, weight is assigned to each criterion to indicate its relative importance. Weighing the criteria should be obtained through a rational process, therefore three factors should be taken into account: the variance degree of criteria, the independency of criteria, and the decision-maker's subjective preference [19]. Mardani et al. [20] reviewed the methodologies and applications of the MCDM techniques and approaches, through investigating a total of 393 articles published from 2000 to 2014 in more than 120 peer-reviewed journals. They categorized those articles into 15 research fields, and found that the "Energy, environment and sustainability" field is ranked as the first field that have applied MCDM techniques and approaches while the "GIS" field was ranked the fifth. They also concluded that the AHP method is by far the most used MCDM technique.

Only one study conducted by the Division of Energy Systems Analysis at the Royal Institute of Technology (KTH) for the International Renewable Energy Agency (IRENA) [21] has been identified to estimate the renewable energy potential in Africa using a GIS-based approach. The study scope generally covered the whole African continent and aimed to identify the technical potential (based on geographic potential and accounting for the losses from conversion into secondary energies and constrained by some requirements related to large-scale installation) for utility-scale solar, wind, and biomass technologies. Although the study [21] took some general exclusion parameters into account, it did not consider other crucial criteria that significantly affect the economic feasibility of installing the proposed renewable energy technologies (e.g. distance to load centres, distance to roads, distance to utility grid ...etc.). Keeping the last discussed point in mind (expecting the study's result to highly overestimate the feasible potential), the study concluded that the Eastern Africa region has the highest technical potential for solar power technologies, with estimates of 175 PWh and 220 PWh annually for Concentrated Solar Power (CSP) and Photovoltaics (PV) respectively. It had been concluded [21] that African countries with the highest CSP and PV potentials are Algeria, Egypt, Namibia, South Africa, Sudan, and Tanzania. The annual technical solar power potential in Tanzania was estimated [21] to be 31,482 TWh for CSP technology and 38,804 TWh for PV technology. It is worth mentioning that the study [21] only used a GIS-approach without integrating it with MCDM techniques.

Most of the studies that combined a GIS-approach with MCDM techniques to identify favourable locations for solar power were applied to small geographical study areas, ranging from a region [22] to a district within a province [23]. Sanchez-Lozano et al. combined a GIS-tool with MCDM methods (AHP method to determine the weights of different criteria, and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method for the final assessment of the alternatives) in order to identify the favourable locations for PV solar power [24] and CSP solar power [25] in a study area near Murcia city, in southeast Spain. Uyan [26] applied GIS complimented by AHP to identify the best sites for solar farms in Karapinar district of Konya Province in the Central Anatolia region of Turkey. Carrion et al.



[23] proposed a methodology that combines AHP with a GIS-approach for selecting optimal sites for grid-connected PV power plants at the Huescar district in the Andalusian region of Spain. Janke [27] used multicriteria GIS modelling techniques to identify areas that are suitable for wind and solar farms in Colorado, USA. Tahri et al. [22] combined GIS-tool with MCDM method to assess the suitability of PV solar power projects in the region of Ouarzazate, south of Morocco.

Only a couple of studies which combined a GIS-approach with MCDM techniques were applied at a country level. Fichter et al. [28] used multicriteria GIS analysis to identify Jordan's favourable locations for CSP, PV, and wind technologies. Charabi and Gastli [29] used the concept of fuzzy quantifiers into the GIS-based land suitability analysis via an Ordered Weighted Averaging (OWA) method to assess the land suitability for PV solar power implementation in Oman. Noorollahi et al. [30] combined GIS analysis with fuzzy AHP to determine the most suitable areas in Iran for locating PV solar power plants. Dawson and Schlyter [31] identified the suitable areas for CSP in Western Australia using a GIS-based analysis complemented by the revised Simos' procedure (MCDM method proposed by Figueira and Bernard [32] to rank site suitability parameters and calculate the numerical weight values).

It is worth noticing that among all the previously mentioned studies that combined GIS-approaches with MCDM techniques, only three studies investigated CSP technology [25,28,31], while all the rest focused only on PV technology. It can be concluded that different studies used different methods and assumptions depending on the objectives of each respective investigation and the chosen approach for tackling the problem. Apparently, there is no comprehensive study in the literature that combined a GIS-approach with MCDM techniques which has been applied to any of the SSA countries (including Tanzania) taking the distinctive local resources and geographical characteristics of this region of the world into consideration.

There is a huge shortage of solar resource assessments in SSA. Consequently, the location suitability for solar power installations is hardly studied in this region of the world. Hence the current study tackles such a research gap by asking the question: "*Where are the most suitable locations in Tanzania to build large-scale solar power installations?*". Answering this research question will potentially contribute to introducing solar energy as a renewable resource for electrification expansion to millions of people who still lack access to electricity.

Determining the most suitable locations for large-scale solar power installations is one of the most important challenges that faces utilities and developers when it comes to introducing and expanding large-scale renewable energy generation. This study aims to assist decision-makers in evaluating suitable areas for large-scale solar power installations by adapting a GIS-MCDM approach. The study contributes to the existing knowledge in this field through introducing:

- the first study to investigate the suitability of large-scale solar power based on integrated GIS-MCDM approach on a country level in SSA,
- technology-specific solar power (CSP and PV) suitability maps for Tanzania at a high resolution of 1 km x 1 km, which represents the highest resolution for any available large-scale solar power suitability maps in SSA,
- distinctive decision clusters and ranking criteria based on in-depth knowledge of the local context in Tanzania (yet with transferability potential to neighbouring SSA countries),
- an approach that is easily applicable to other renewable energy technologies once the corresponding criteria (that represent the respective technology) have been carefully identified,

- an approach which is applicable on a country level, yet informs regional energy decision-makers and developers as well.

## 2. Material and methods

In this study GIS-analysis combined with MCDM technique have been applied to identify the hot spots (i.e. specific recommended locations) for the large-scale solar power installations in Tanzania. This section will be divided into two main sub-sections which represent the two-step process used to identify the hot spots; firstly relevant Exclusion Criteria (EC) used to mask unsuitable areas for large-scale solar power will be explained, then the AHP method (one of the MCDM techniques) will be used to weigh the Decision Clusters (DC) and their Ranking Criteria (RC). Fig. 1 summarizes the applied methodology that will be explained hereafter. All digitization, conversion, and analysis of the spatial data were performed using the Environmental Systems Research Institute (Esri) commercial software ArcMap (version 10.3.1), the AHP pairwise calculations have been computed using the BPMSG AHP priority calculator (utilized under the Creative Commons Attribution-Noncommercial 3.0 Singapore License). Finding required input data for this study with high degree of certainty was not an easy task, many relevant international institutions have been contacted and meetings with officials from many Tanzanian institutions have been held aiming to obtain the most authentic and updated data.

It is worth mentioning that some exclusion and ranking criteria are technology specific, in this study the parabolic troughs CSP technology (i.e. the most commercially mature CSP technology) and the crystalline silicon PV technology (i.e. the most common PV technology) have been considered. Such decision to consider the most commercially available solar technology is based on qualitative interviews conducted by the first author in the summer of 2016 with representatives from governmental institutions, research institutions, private sector, local and international NGOs, and development partners (see Appendix B). Based on these interviews, it could be concluded that Tanzania will start by integrating the most commercially available solar technology rather than adapting some new cutting-edge solar technologies which are usually more capital intensive and require highly qualified professionals to design, operate, and maintain (referring to interviews no. 1, 2, 3, 6, 8, 9, 12, 15, 19, 20, 21, 22, and 26 listed in Appendix B).

### 2.1 Excluding unsuitable areas

The first step of the GIS-analysis is to exclude those areas which are unsuitable for installing large-scale solar power plants. Identifying the exclusion criteria usually depends on availability of the spatial data and the geographical coverage of the study area (district, national, regional, or continental). As the study is conducted on a country level, the following Exclusion Criteria (EC) are desirable: protected areas (EC1), land cover (EC2), topography (EC3), water bodies (EC4), urban expansion (EC5), and low solar radiation (EC6). Compared to relevant and specialized literature [12,21,31], the exclusion criteria taken into consideration in this study are comprehensive. The following paragraphs will elaborate on each of the six identified exclusion criteria (EC 1-6).

#### Protected areas (EC1)

The information on the protected areas is based on data provided by the World Database on Protected Areas (WDPA) [33] which is a joint project between the United Nations Environment Programme (UNEP) and the International Union for Conservation of Nature (IUCN), managed by UNEP World Conservation Monitoring Centre (UNEP-WCMC). The dataset contains protected areas designated at the national level and under regional and international conventions and agreements. According to IUCN's definition, a

protected area “is a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long term conservation of nature with associated ecosystem services and cultural values”. IUCN has defined a series of six protected area management categories, based on primary management objective. All the protected areas of Tanzania including national and the six IUCN protected area management categories have been excluded.

#### **Land cover (EC2)**

As large-scale solar power requires relatively large areas of land compared to other electricity generation technologies, it is important to identify lands with no other potential productive land uses. The information on the land cover is based on the European Space Agency’s (ESA) GlobCover Database 2009 [34]. The ESA GlobCover map has a spatial resolution of 10 x 10 arc-seconds (i.e. 300 m x 300 m) and is classified in 23 categories. Among the 23 land categories, only four categories have been considered as suitable for potential large-scale solar power installations. Those categories correspond to the values of 30, 140, 150, and 200 at GlobCover legend, means lands with dominant mosaic vegetation, herbaceous, sparse vegetation, and bare areas. For detailed description and characteristics of each of the 23 land categories refer to Appendix II of [34]. Considering only the four aforementioned categories represents a conservative approach, as it can be argued that solar power installations should not compete on land classified as: cultivated or managed land, woody and trees, shrub, and natural aquatic vegetation. Such constraints could be relaxed to allow other land uses in future research if advanced national land management strategy (e.g. combining two land uses) would have been adopted.

#### **Topography (EC3)**

In general, it is highly favourable for large-scale solar power plants to be constructed on flat terrain. For CSP plants, especially parabolic trough power plants, flat terrain is required. A slope higher than 2.1% is excluded for building CSP plants. There is almost a consensus in the literature that for parabolic trough CSP plants areas with ground slope higher than 2.1% are considered to be unsuitable [35,36]. There is no consensus in the literature regarding the accepted slope percentage for PV plants. Uyan [26] excluded lands with slopes higher than 3%, Charabi and Gastli [29] excluded lands with slopes higher than 5%, Cohen et al. [37] excluded lands with slopes higher than 5.24%, and Noorollahi et al. [30] included the slope as one of the ranking criteria and excluded lands with slopes higher than 11%. Semi-flat terrain is highly favourable for solar exposure and constructability, building a large-scale PV plant on land with steep slopes leads to significant increase in the project capital and maintenance costs. Similar to Uyan [26] a conservative threshold was used, given the local economic and technological context of Tanzania. Hence in this study lands with slopes higher than 3.0% were excluded for building PV plants.

The slope map was derived from the Digital Elevation Model (DEM) of the NASA Shuttle Radar Topographic Mission (SRTM) obtained through CGIAR-CSI GeoPortal [38] by applying spatial analysis tools available through the used GIS software. The DEM-SRTM data was provided with a spatial resolution of 90 m at the equator.

#### **Water bodies (EC4)**

The information about the water bodies is based on data provided by the Global Lakes and Wetlands Database (GLWD) which has been developed by Lehner and Doll [39] in a partnership between the Center for Environmental Systems Research (CESR), University of Kassel, and World Wildlife Fund US (WWF-US). The GLWD consists of three data sets GLWD 1-3, the GLWD-3 data set has been used which includes 12 water bodies and wetlands categories (e.g. large lakes, reservoirs, rivers, other water bodies, and wetlands) at spatial resolution of 30 x 30 arc-seconds (i.e. 900 m x 900 m). All categories from the GLWD-3 dataset have been used as exclusion mask for large-scale solar power sites.

## Urban expansion (EC5)

Tanzania is a country with high population growth, the 2002 census indicated around 35 million people while the 2012 indicated around 45 million people [40]. In 2016, Tanzania's population was estimated to 55 million people [41]. Within the lifetime of large-scale solar power installations (approx. 25 years) expected to be commissioned within the coming decade, by 2050 Tanzania's population is expected to reach 137 million people [41]. Hence the urban population is expected to be tripled by 2050. In the future, the existing urban centres are not only expected to expand horizontally but vertically as well (a trend obviously seen in Dar es Salaam and other main cities) to accommodate the increasing population.

Inhabitants of the cities with current populations exceeding 250,000 live within an area of 80 km<sup>2</sup>, hence this study -based on the foreseen urban expansion by 2050- excluded areas within 8 km from these cities (approx. 201 km<sup>2</sup>). Similarly, inhabitants of the cities with current population between 100,000 and 250,000 live within an area of 40 km<sup>2</sup>, hence this study excluded areas within 6 km from these cities (approx. 113 km<sup>2</sup>). The information on the current population of Tanzania's cities is based on data provided by the World Population Review [41], then own spatial data were generated at spatial resolution of 0.01 x 0.01 decimal degrees (i.e. 1 km x 1 km).

## Low solar radiation (EC6)

For large-scale solar power installations to be economically viable, they should be built on areas that receive significant solar radiation. Almost all commercial CSP plants have been built on sites with annual Direct Normal Irradiance (DNI) more than 1800 KWh/m<sup>2</sup>, and almost all commercial utility-scale PV plants have been built on sites with annual Global Horizontal Irradiance (GHI) more than 1700 KWh/m<sup>2</sup>. Hence in this study areas with annual DNI less than 1800 KWh/m<sup>2</sup> have been excluded for CSP installations, and areas with annual GHI less than 1700 KWh/m<sup>2</sup> have been excluded for PV installations. The information on the solar resource assessment is based on data provided by a study conducted by Spain's National Renewable Energy Centre for the World Bank Group [42] at 0.05° spatial resolution (i.e. 5 km x 5 km).

A series of exclusion layers was created based upon the aforementioned exclusion criteria. All layers representing exclusion criteria were combined via raster calculation GIS-tool and resulted in the overall technology-specific exclusion mask. Data-processing was conducted at a spatial resolution of 1 km x 1 km, the low solar radiation (EC6) layer was the only integrated layer with a lower resolution. Only areas which are not excluded due to any of the six exclusion criteria will be considered as available areas for large-scale solar power installations. Fig. 2(a) shows the exclusion mask for CSP installations, while Fig. 2(b) shows the exclusion mask for PV installations. White-coloured areas represent the available areas for the respective technology.

## 2.2 Ranking suitable areas

After excluding the unsuitable areas for large-scale solar power installations, MCDM technique has been used to identify the CSP and PV hot spots within the available areas. The selection of the ranking criteria is an essential step, followed by determining credible and justifiable weights for each of the decision criterion that shows the preferences of each criterion as a reflection of the decision-maker's interests.

### 2.2.1 Ranking criteria

The ranking criteria and their tiers scoring have been carefully identified based on insights from relevant literature [10-12,15,22-31,43], the study's objective, the study's spatial scale, and the first author's understanding of the local Tanzanian context (based on many interviews held in Tanzania with relevant stakeholders and decision makers in the summer of 2016, see Appendix B). In total seven Ranking Criteria (RC) have been identified: solar resources (RC1), water availability (RC2), proximity to roads (RC3), proximity to utility grid (RC4), proximity to cities with over 250,000 inhabitants (RC5), proximity to cities with 100,000 to 250,000 inhabitants (RC6), and proximity to mines (RC7).

The number of tiers for each RC is determined distinctively based on the relative importance of each tier within each RC. For instance, the threshold of 50 kWh/m<sup>2</sup> annually has been identified for RC1 as it indicates a significant change of the solar radiation which influences the electricity generation of a large-scale solar power installation [28]. This lead to defining 8 tiers for "RC1 - Annual DNI" and 12 tiers for "RC1 - Annual GHI", as the highest annual DNI value of the obtained DNI map [42] is within 2,150 kWh/m<sup>2</sup> and 2,200 kWh/m<sup>2</sup> while the highest annual GHI value of the obtained GHI map [42] is within 2,250 kWh/m<sup>2</sup> and 2,300 kWh/m<sup>2</sup>. To elaborate on another example, the threshold of 5 Km has been identified for RC3 as it indicates a significant change of the cost required for constructing a new road [28]. Sites more than 20 Km away from existing road will require prohibitive cost for constructing dedicated roads, hence are totally unfavourable. Consequently, 5 tiers have been identified under RC3.

A quantitative scoring was assigned to each tier representing its relative favourability to have a large-scale solar power installation [the least-favourable tier is assigned a value of 0, while the most-favourable tier is assigned a value of 100]. The scale of 0 to 100 is only a representative relative scale (i.e. it could be replaced by a scale of 0 to 10), as it will afterwards be subjected to the application of the MCDM method explained in details in section 2.2.2.

### **Solar resources (RC1)**

Solar radiation is the primary resource for solar power technologies. The DNI is the primary resource for CSP technologies, according to NASA Surface meteorology and Solar Energy department, DNI is "the amount of electromagnetic energy (solar radiation) at the Earth's surface on a flat surface perpendicular to the sun's beam with surrounding sky radiation blocked". On the other hand, the GHI indicates the primary resource for PV technologies, GHI is the total amount of shortwave radiation received on horizontal surface at the ground. GHI includes both DNI and Diffuse Horizontal Irradiance (DIF) which is solar radiation that does not follow a direct path from the sun, but has been scattered by particles and molecules in the atmosphere and therefore comes from all directions. Sites with high solar resources potential will have a significant impact on the economic feasibility of large-scale solar power installations, hence it is essential to consider locations with high DNI for CSP installations and locations with high GHI for PV installations.

The information on the solar resources in Tanzania is based on data provided by Energy Sector Management Assistance Program (ESMAP) of the World Bank Group. The GIS data was prepared by Spain's National Renewable Energy Centre under contract to the World Bank Group [42] at 0.05° spatial resolution (i.e. 5 km x 5 km).

The obtained DNI and GHI maps have been reclassified to represent intervals with 50 kWh/m<sup>2</sup> annual radiation difference. Fig. 3(a) shows the reclassified DNI map, while Fig. 3(b) shows the reclassified GHI map. While CSP plants can operate at annual DNI level of 1,800 kWh/m<sup>2</sup> and large-scale PV plants can operate at annual GHI level of 1,700 kWh/m<sup>2</sup>, the plant's location becomes much techno-economically

favourable with increased radiation levels. Table 1 shows the quantitative scoring assigned to the eight DNI tiers and the twelve GHI tiers.

### **Water availability (RC2)**

The considered parabolic trough CSP technology often utilizes the thermal energy generated through the solar field to drive a steam turbine, hence a water requirement for cooling such CSP plant is similar to that of any Rankine cycle-based plant. Although dry-cooling of CSP plants is technically feasible, it leads to lower overall plant efficiency and higher capital cost. According to the US National Renewable Energy Laboratory (NREL) [44], a wet-cooled parabolic trough CSP plant consumes on average 3,274 l/MWh, most of the water is used for the cooling processes of the steam cycle (approx. 90%) and a small amount (approx. 10%) is used for mirror washing and boiler blowdown. Consequently, CSP plants are highly recommended to be built near water sources with high stream flow. In this study, only main lakes in Tanzania were considered as eligible water sources to feed wet-cooled CSP plants in order to avoid competing with irrigation needs from small rivers and streams. PV plants require minimal amount of water (that could be transported) mainly for cleaning purposes, hence the water availability (RC2) is considered among the ranking criteria for CSP installations only.

The information on water resources is based on data provided by the GLWD [39]. The database has been generated through the use and incorporation of data derived from proprietary products of Esri and the UNEP World Conservation Monitoring Centre (UNEP-WCMC). The CSP plant's location becomes much techno-economically favourable being near to water sources with high stream flow. Table 1 shows the quantitative scoring assigned to the five tiers that represent the proximity to water sources.

### **Accessibility**

The accessibility cluster includes proximity to roads (RC3) and proximity to utility grid (RC4) as indicators of the existing infrastructure which facilitate the construction and the integration of large-scale solar power plants. Considering large-scale solar power installation in location with low accessibility leads to a significant increase in the capital expenditures, resulting in additional cost to the already high upfront investment of such projects.

### **Proximity to roads (RC3)**

Vehicle access to the solar plant's site is crucial for constructability and maintenance purposes. Hence the proximity of a solar plant to existing road is considered an economic factor through avoiding the additional cost of road construction and its associated damage to the environment. The information about road infrastructure is based on data compiled by Africon Limited for on the Africa Infrastructure Country Diagnostic (AICD) study led by the World Bank [45]. Only trunk roads have been taken into consideration, as the construction of large-scale solar power installations require massive equipment which is usually transported by trucks. The trunk roads have been validated against the most recent map from Tanzania National Roads Agency (TANROADS) available at its official website on December 2016. Locations nearer to existing trunk roads are favoured over those far from existing trunk roads network. Table 1 shows the quantitative scoring assigned to the five tiers that represent the proximity to roads.

### **Proximity to utility grid (RC4)**

Large-scale solar power requires access to transmission grid, and the grid connection is usually performed on a high voltage level. Considering the high cost associated with constructing power transmission lines, the proximity to existing transmission line helps in avoiding additional capital cost and power losses. The information on utility grid routes is based on the Africa Infrastructure Country Diagnostic (AICD) study led by the World Bank [45]. Only high voltage transmission lines (132 kV and 220

kV) have been taken into consideration, and they have been validated against the most recent National Grid System map developed by Tanzania Electric Supply Company Limited (TANESCO) on May 2016. Locations nearer to existing transmission grid are favoured over those far from transmission grid. Table 1 shows the quantitative scoring assigned to the nine tiers that represent the proximity to the utility grid.

### **Demand**

The demand cluster includes proximity to cities with over 250,000 inhabitants (RC5), proximity to cities with 100,000 to 250,000 inhabitants (RC6), and proximity to mines (RC7) as indicators of demand centres. Considering large-scale solar power installation in location near to demand centre reduces transmission losses over utility grid, on the other hand proximity to demand centre is very desirable for autonomous isolated-grids that feed loads far from existing utility grid.

#### **Proximity to cities with over 250,000 inhabitants (RC5)**

Electricity generated near a big city with a population over 250,000 inhabitants is favourable. A short distance between supply and demand reduces the congestion in the transmission network, reduces power losses, and minimises transmission cost through avoiding the need for lengthy and costly transmission lines. Another socio-economical factor when building large-scale solar power installations is the availability of local labour from nearby big cities. The information on cities with population over 250,000 inhabitants is based on data provided by World Population Review [41]. Locations nearer to big cities are favoured over those very far from them. Table 1 shows the quantitative scoring assigned to the five tiers that represent the proximity to cities with a population over 250,000 inhabitants.

#### **Proximity to cities with 100,000 to 250,000 inhabitants (RC6)**

Some cities with a population between 100,000 and 250,000 inhabitants in Tanzania are relevant load centres for autonomous isolated-grids, especially when they are far from an existing utility grid. The threshold of 100,000 inhabitants is considered as sufficiently large load must be available to promote the investment in large-scale solar plants. The information on cities with population between 100,000 and 250,000 inhabitants is based on data provided by World Population Review [41]. Locations nearer to cities between 100,000 and 250,000 inhabitants are favoured over those very far from them. Table 1 shows the quantitative scoring assigned to the six tiers that represent the proximity to cities with a population between 100,000 and 250,000 inhabitants.

#### **Proximity to mines (RC7)**

Tanzania is endowed with plentiful mineral resources, it possess the second largest gold reserves in Africa [46]. The main energy concern of mining companies is the security of supply. This explains the decisions of many mining companies to invest in self-supply even when the cost per kWh delivered is much higher to ensure security and continuous power availability. In Tanzania, the modest performance and financial situation of TANESCO encourages many mines to move into a self-supply mode. It is worth mentioning that mines with reasonable production capacity represents enough load that qualify it as a viable (financially stable) off-taker of electricity generated by large-scale solar power projects, hence justifying the invest in such projects. Therefore, big mines are considered major demand indicators in Tanzania.

The main concern in this regard is the potential impact of mines' lifetime on the feasibility of the large-scale solar power installation. The lifetime of a mine is usually difficult to predict due to uncomplete exploration of the resource (as resource exploration is expensive, it is not often undertaken according to clear plans), and it is often subject to corporate confidentiality restrictions for some investment and



taxation reasons. Consequently, expected mine lifetimes being continually upgraded while further exploration takes place. In addition, mine's commercial lifetime is also affected by the international commodity price.

The assessment of the lifetimes of Tanzania's mines goes beyond the scope of this study. Hence only four gold mines which seems of reasonable production capacity and expected to have a relatively long lifetime (as indicated by their respective mining companies) were considered. The selected mines are: Geita Gold Mine (owned by AngloGold Ashanti), Bulyanhulu Gold Mine and North Mara Gold Mine (owned by Acacia Mining), and New Luika Gold Mine (owned by Shanta Mining Company Limited). It is worth mentioning that the four considered gold mines are located in areas within CSP exclusion mask, hence the proximity to mines ranking criterion is consider among the ranking criteria for PV installations only. Locations nearer to mines are favoured over those far from them. Table 1 shows the quantitative scoring assigned to the four tiers that represent the proximity to mines.

All layers representing ranking criteria have been developed through GIS-processing at a spatial resolution of 1 km x 1 km, except the DNI map and GHI map (i.e. solar resources ranking criteria) which was provided at spatial resolution of 5 km x 5 km. Fig. 3 spatially shows the different tiers of each ranking criterion.

### 2.2.2 Applying the Analytic Hierarchy Process (AHP) method

Historically, the equal criteria weights method was a very popular weighting method [15], but recently the AHP became the most used MCDM method tackling energy system problems. The AHP was chosen to handle the problem addressed in this study because it allows for qualitative evaluation, for the ranking criteria to be assigned weights that represents decision-making preference, and for conducting a sensitivity analysis of the results through alternative input assumptions that represent different potential scenario (e.g. another decision-making preference according to different stakeholder's interests).

The oldest reference for the AHP method appeared in the literature dated back to 1972 [47]. In 1977, Saaty clearly described the method in a paper published at the Journal of Mathematical Psychology [48]. In [49], Saaty explained how to make a decision using AHP, and some applications of the AHP in industry and government have been summarized by Vargas [50]. In [51], Ishizaka et al. reviewed the methodological developments of the AHP since its inception. The AHP is a multicriteria decision making method that compare decision criteria through a pairwise criteria comparison to obtain favourability scale among a set of alternatives [50]. Before applying the AHP method to a problem, the problem should be represented in a hierarchical structure that includes all the factors (i.e. criteria) that represent the interests of the decision-maker. All the identified decision criteria are compared against each other in a form of pairwise comparison matrix that represents a way to assign the relative preferences among the different factors. Saaty [48] suggested a comparison scale consisting of values ranging from 1 to 9 which represent the significance of the importance, e.g. while a value of 1 represents "equal importance", a value of 9 is assigned to those factors having an "absolute importance" over another factor (see Table 2). Then to obtain the criteria weights, the eigenvalues and the eigenvectors of a square preference matrix (i.e. which contains the quantified preference information) have to be calculated (see Appendix A). In this section the application of AHP to a general problem of three decision criteria will be explained. For further detailed elaboration on the AHP, the reader is referred to [49,51].

Applying the AHP model goes through sequential steps which include: selecting decision clusters and ranking criteria, conducting pairwise comparison at the clusters and criteria levels, performing

consistency checks, and finally determining the criteria relative weight. The decision criteria weighting were divided into two levels as shown in Fig. 1. The rationale behind this hierarchy of the criteria is to present a higher decision-making criteria level that could be subjected to sensitivity analysis to reflect the interest of different stakeholders (i.e. demand-driven scenario explained in the results and discussion section).

When AHP is used, usually a group of experts are asked to preliminary assign criteria's weights. To assign criteria's weights some studies [22,24,25,29,30] relied on a number of experts to compare the criteria based on linguistic labels. Similar to judgmental sampling, the more involved experts the better, and it is essential to select experts who are very specialized in the technology and are very knowledgeable about the local context. Sanchez-Lozano et al. [25] relied only on three experts (doctor engineers in the field of renewable energy), while Noorollahi et al. [30] relied only on four experts from governmental, industrial, and academic institutions.

Apparently, there are very few local experts in Tanzania who are specialized in this field. This finding is based on 27 qualitative interviews conducted by the first author through snowball sampling in the summer of 2016 with representatives from governmental institutions, research institutions, private sector, local and international NGOs, and development partners (see Appendix B). Consequently, it is more useful to rely on an extensive literature review [that already reached criteria weights based on expert opinion and processed through AHP or fuzzy AHP] rather than depending on either a handful of highly qualified international experts who are not knowledgeable enough about the Tanzanian local context, or a handful of local people who are knowledgeable about the Tanzanian local context but not specialized in CSP and PV technologies. The concluded comparison between different Decision Clusters (DC) and Ranking Criteria (RC) has been represented in the form of linguistic labels following the Saaty's discrete 9 value scale [48] shown in Table 2.

To briefly elaborate on a general problem of three decision criteria, matrixes of pairwise comparisons (based on Saaty's discrete 9 value scale) were created.

$$X_p = \begin{bmatrix} 1 & a & b \\ 1/a & 1 & c \\ 1/b & 1/c & 1 \end{bmatrix} \dots (1)$$

The relative weights of X1, X2, and X3 can be determined from matrix X by normalizing it into a new matrix (i.e.  $X_N$ ) through dividing the elements of each column by the sum of the elements of the same column. The relative weights of three alternatives are then computed as the row average of the new matrix. Mathematically, the matrix X is consistent if:

$$x_{ij} \times x_{jk} = x_{ik} \dots (2)$$

A reasonable level of inconsistency is expected and tolerated. To determine whether the level of inconsistency is 'reasonable', Saaty [49] recommended to estimate the Consistency Index (CI) using

$$CI = \frac{\lambda_{max} - n}{n - 1} \dots (3)$$

where n is the size of the matrix ( $n \times n$ ) and  $\lambda_{max}$  is the product of  $X_p$  and  $N_p$ . The Consistency Ratio (CR) can be estimated using

$$CR = \frac{CI}{RC} \dots (4)$$

where the Random Consistency (RC) of the matrix X is estimated using a standard table developed by Saaty [52].

If the CR value is equal to or less than 0.10 (i.e. 10%), the pairwise comparison results are acceptable, otherwise they should be revised. Appendix A elaborates on the application of AHP to Decision Clusters (DC) and to the Ranking Criteria (RC) of each decision cluster. Table 3 shows the decision clusters weights and ranking criteria overall weights obtained through applying AHP method for CSP and PV technologies.

The integration between the GIS and MCDM analyses has been performed based on weighted sum model [53] (i.e. a simple model to evaluate the objective function in terms of a number of decision criteria -each has its distinctive relative weight- through summing the criteria's weighted values). GIS-processing has been conducted to obtain final values of the objective function at each pixel (1 km x 1 km), Equation (5) summarizes the performed calculation.

$$s = \left( \sum_{i=1}^7 w_i \cdot RC_i \right) \cdot \prod_{j=1}^6 EC_j \quad \dots (5)$$

where  $s$  is the objective function representing the final suitability of any given location,  $i$  is the counter of the RC,  $j$  is the counter of the EC, and  $w_i$  represents the respective assigned weight to each of the RC.

A GIS-tool was used to superimpose all the reclassified raster maps, then each of those maps have been multiplied by the assigned overall weight of the respective ranking criteria and summed together. Finally, the technology specific exclusion masks have been applied resulting in a final technology-specific ranked suitability map.

### 3. Results and discussion

Fig. 4(a) shows the overall suitability for CSP power plants throughout all regions of Tanzania, while Fig. 4(b) shows the overall suitability for PV power plants. For CSP, it is clear that the Dodoma region and Singida region are the most favourable, besides few locations in the Iringa region and Tabora region. All the favourable regions for CSP installations are also favourable for PV installations, besides the Shinyanga region and Mwanza region which are particular favourable for PV installations.

The resultant maps -after applying the weighted sum model- have been reclassified through a GIS-tool to categorize each of the non-excluded areas into four categories: most suitable, suitable, moderately suitable, and least suitable. The areas designated as most suitable, suitable, and moderately suitable represents the pixels corresponding to values higher than 80%, 60%, and 35% of the highest suitability value (resulting from equation 5) respectively. While the areas designated as least suitable represents the pixels corresponding to values less than 35% of the highest suitability value.

Fig. 5(a) shows the CSP ranked suitability map, while Fig. 5(b) shows the PV ranked suitability map. For CSP installations, 3,584 km<sup>2</sup> were designated as most suitable, 21,523 km<sup>2</sup> were designated as suitable, and 20,184 km<sup>2</sup> were designated as moderately suitable. For PV installations, 20,801 km<sup>2</sup> were designated as most suitable, 68,848 km<sup>2</sup> were designated as suitable, and 78,133 km<sup>2</sup> were designated as moderately suitable.

Fig. 5(a) demonstrates that the suitability of CSP installation is highly dependent on solar resource availability (i.e. highest DNI levels between Dodoma and Iringa), and water availability (i.e. areas near

Mtera Reservoir and Sulunga Lake). The accessibility of the site (e.g. proximity to roads and utility grid) also plays a role in favouring some locations (i.e. cities like Dodoma, Mwanza, Shinyanga, Tabora, and Iringa are well linked to roads and grid infrastructure), and proximity to big cities favour the surrounding areas further as they indicate demand centres. Fig. 5(b) demonstrates that the suitability of PV installations is highly dependent on solar resource availability (i.e. highest GHI levels between Dodoma and Iringa). It is clear that the accessibility of the site plays a role in favouring some locations within high solar radiation zones even further (e.g. the route between Dodoma and Shinyanga reflect the existence of roads and grid infrastructure). Although the GHI is reduced while moving northward, the existence of roads and grid infrastructure on the route from Mwanza through Shinyanga to Tabora favours adjacent locations for PV installations.

Hot spots represent specific areas where building a technology-specific plant are considered of the highest techno-economic favourability according to the selected decision criteria and their relative importance to the decision maker. Four hot spots for CSP installations were identified: in Dodoma region near Dodoma city (CSP-HS1) and near Mtera Reservoir (CSP-HS2), in Singida region near Sulunga Lake (CSP-HS3), and in Iringa region near Iringa's Nduli Airport (CSP-HS4). Four hot spots for PV installations were identified: in Dodoma region near Dodoma city (PV-HS1), in Singida region near Singida town (PV-HS2), in Shinyanga region near Shinyanga city (PV-HS3), and in Iringa region near Iringa city (PV-HS4). Fig. 6 shows the identified CSP and PV hot spots.

Conducting a sensitivity analysis is highly recommended for problems that include inputs based on non-certain assumptions. The decision criteria weighting were divided into two levels, then the higher decision-making criteria level (Decision Clusters) could be subjected to sensitivity analysis. The Base Case Scenario represents the interest of the government (as the owner of the vertically-integrated utility monopoly TANESCO) as the prime decision-maker, hence the centralized solution is favoured (i.e. the objective function is to integrate large-scale solar power wherever it is technically suitable and economically favourable with minimal attention to building the solar plants near specific load centres). Consequently, the weight of accessibility decision cluster (DC3) was approximately three times the weight of the demand decision cluster (DC4).

The most critical view about using a combined GIS-MCDM methodology to solve a problem similar to the one addressed in this study is the associated uncertainty on both input data and weighting of the criteria, which has a strong influence on the final outcomes [54]. Hence sensitivity analysis has been conducted through considering another potential scenario which represents another decision-maker preference (i.e. different stakeholder's interests).

The Demand-driven Scenario represents the insert of some large-scale solar power developers who are interested in feeding certain load centres (e.g. mines or big cities), hence the decentralized solution is favoured. The whole procedures of applying the AHP method has been repeated to calculate the decision clusters weights and ranking criteria overall weights for the Demand-driven Scenario shown in Table 4. Fig. 5(c) shows the CSP ranked suitability map according to the Demand-driven Scenario, while Fig. 5(d) shows the PV ranked suitability map according to the Demand-driven Scenario. Although some marginal differences appears when comparing the suitability maps of the Base Case Scenario with the suitability maps of the Demand-driven Scenario, the main identified hot spots for CSP and PV are still very relevant. This shows that the used methodology is consistent and reliable as the absolute objective (the identified hot spots) is robust regardless small uncertainties within the input parameters.

Regarding the final classification of the technology-specific suitability maps, it must be admitted that the determination of the thresholds remains difficult. Assigning the thresholds for the final site suitability used by this study is -to some extent- arbitrary. The results of this study suggest, for instance, that a location in a “moderately suitable” area is less suitable for CSP/PV installation than a location in “most suitable” area. Yet the results do not suggest that CSP/PV plant is necessarily always feasible at locations in “most suitable” area, and not feasible at locations in “least suitable” area, nor do they suggest that a location with an aggregate final score of 90% (of the highest suitability value), for instance, is fully three times more suitable than a site with an aggregate final score of 30% (of the highest suitability value).

The existence of infrastructure (road or transmission line) does not necessarily mean it is available. Throughout this study an assumption has been made that wherever infrastructure exists, it is available (i.e. the unlimited possibility to use it). However, there may be some capacity restrictions in transmission lines of the utility grid, which could introduce a potential obstacle for integrating a new large-scale solar power plant although located adjacent to an existing transmission line. A dedicated capacity restriction assessment for all infrastructural components is beyond the scope of this study, consequently the final results do not account for such restrictions.

Tanzania has a vision to become a middle income country by 2025, hence many roads and grid extensions are expected. As the placement of large-scale solar power installations is affected by the availability of roads and grid infrastructure, building new roads and extending the utility grid will introduce new suitable areas for large-scale solar power in Tanzania. Among the strengths of the used methodology is that it allows easily to update the input data (as long as more recent data become available or planned infrastructure needed to be taken into consideration), it also allows a high degree of flexibility to update final suitability maps in accordance to new decision-makers’ preferences (e.g. new government’s preferences).

The combined GIS-MCDM methodology presented in this paper is applicable to similar analyses in other regions and for evaluating the spatial suitability of other renewable energy technologies as long as their respective criteria (that represent technological factors, account for the local context, and represent distinctive decision-makers’ preferences) have been carefully identified.

When applying the presented GIS-MCDM methodology to other regions or countries, identifying the most-relevant criteria for conducting an informative analysis depends mainly on the data availability and the required complexity level of the analysis which is often linked to the spatial scale of the analysed area (e.g. state, country, continent ...etc.). In general, data availability is one of the main obstacles that hinders the strategic energy planning in many of the developing country (including SSA countries). In developed countries, where more comprehensive well-documented GIS data with high-resolution are available, some other criteria can be included to represent other infrastructure and other existing -or future- land uses. Examples could be distance to civil and military airports (as local and international regulations indicate the types of permissible constructions near airports to ensure flights safety), bird migratory routes (to minimize or avoid potential bird fatalities caused by solar installations, being CSP or PV plants), military reservation lands, aquifers, and proximity to auxiliary fuels (in case that CSP fuel hybridization option is considered, auxiliary fossil fuel-driven boiler, usually fuelled by natural gas, is required). More in-depth economic-focused and social-focused criteria can also be considered, -for instance- if a continent/federal country is analysed which includes distinctive “financial incentives” or “social acceptance levels” for renewables (or solar) projects in each country/state.

#### 4. Conclusions

One of the main concerns regarding large-scale solar power installations is their high up-front investment, hence identifying the best location for installing a solar power plant is considered among the most important steps in the development of this industry. Multiple techno-economic criteria have been used to identify the most suitable locations for hosting solar power installations in Tanzania. A combination of GIS-analysis and MCDM techniques has been applied to identify the large-scale solar power technology-specific hot spots in Tanzania. Apparently, based on an extensive literature review, this is the first study to assess site suitability for large-scale solar power installations using combined GIS-MCDM approach on a country level (Tanzania) in Sub-Saharan Africa –where more than 600 million people still do not have access to electricity-.

*“Where are the most suitable locations in Tanzania to build large-scale solar power installations?”* was the main research question that this study tackled. The careful selection of the decision clusters and the ranking criteria which reflects the local context (e.g. decision-maker's preferences) very well was the key to achieve reliable results.

Through informed selection of the decision clusters and the ranking criteria which accounts for the local context, the study identified six exclusion criteria (i.e. protected areas, land cover, topography, water bodies, urban expansion, and low solar radiation) to mask unsuitable areas. Four decision clusters have been considered (i.e. solar resources, water availability –only applied to CSP-, accessibility, and demand). Under the accessibility decision cluster two ranking criteria have been identified (i.e. proximity to roads, and proximity to utility grid), while under the demand decision cluster three ranking criteria have been identified (i.e. proximity to cities with over 250,000 inhabitants, proximity to cities with 100,000 to 250,000 inhabitants, and proximity to mines –only applied to PV-). The Analytic Hierarchy Process has been used to determine the relative weights of the decision clusters and the final weights of the ranking criteria.

Sensitivity analysis has been conducted through considering the Demand-driven Scenario (i.e. favouring decentralized solutions) which represents the interest of some large-scale solar power developers who are interested in feeding certain load centres (e.g. mines or big cities).

The analysis concluded that for CSP installations, 3,584 km<sup>2</sup> in Tanzania was designated as most suitable, 21,523 km<sup>2</sup> was designated as suitable, and 20,184 km<sup>2</sup> was designated as moderately suitable. For PV installations, 20,801 km<sup>2</sup> was designated as most suitable, 68,848 km<sup>2</sup> was designated as suitable, and 78,133 km<sup>2</sup> was designated as moderately suitable. The study also identified four hot spots (i.e. specific recommended locations) for CSP installations and four hot spots for PV installations.

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## Appendix A

AHP calculations for determining weights of Decision Clusters (DC) and Ranking Criteria (RC)

## Appendix B

Interviews list

## Figure Captions

**Fig. 1.** Methodology model.

**Fig. 2.** Large-scale solar power technology-specific exclusion mask for (a) CSP installations and (b) PV installations.

**Fig. 3.** Tiers of (a) annual DNI, (b) annual GHI, (c) proximity to water sources, (d) proximity to roads, (e) proximity to utility grid, (f) proximity to cities with over 250,000 inhabitants, (g) proximity to cities with 100,000 to 250,000 inhabitants, (h) proximity to mines.

**Fig. 4.** Overview of (a) CSP and (b) PV suitability on all regions of Tanzania (black colour represent unsuitable areas and white colour represents most suitable areas), final images generated using Google Earth™

**Fig. 5.** Large-scale solar power ranked suitability maps of the Base Case Scenario for (a) CSP and (b) PV, and of the Demand-driven Scenario for (c) CSP and (d) PV.

**Fig. 6.** CSP and PV hot spots.

Title:

Solar Power Potential of Tanzania: Identifying CSP and PV Hot Spots through a GIS Multicriteria Decision Making Analysis.

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Second Author: **Steen Solvang Jensen**

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**Table A.1**

AHP applied to Decision Clusters (DC)

Decision Clusters (DC)	Decision Matrix	Principle Eigen Value	Eigenvector Solution	Consistency Ratio (CR)
<i>CSP technology</i>				
$\begin{bmatrix} \text{Solar Resources (DC1)} \\ \text{Water Availability (DC2)} \\ \text{Accessibility (DC3)} \\ \text{Demand (DC4)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 4.00 & 6.00 & 8.00 \\ 0.25 & 1.00 & 2.00 & 5.00 \\ 0.17 & 0.50 & 1.00 & 5.00 \\ 0.12 & 0.20 & 0.20 & 1.00 \end{bmatrix}$	4.202	5 iterations delta = 1.0E-7	7.4%
<i>PV technology</i>				
$\begin{bmatrix} \text{Solar Resources (DC1)} \\ \text{Accessibility (DC3)} \\ \text{Demand (DC4)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 4.00 & 7.00 \\ 0.25 & 1.00 & 4.00 \\ 0.14 & 0.25 & 1.00 \end{bmatrix}$	3.076	4 iterations, delta = 4.2E-8	8.0%

**Table A.2**

AHP applied to Ranking Criteria (RC) of each decision cluster

Ranking Criteria (RC)	Decision Matrix	Principle Eigen Value	Eigenvector Solution	Consistency Ratio (CR)
<i>CSP technology</i>				
$\begin{bmatrix} \text{proximity to road (RC3)} \\ \text{proximity to utility grid (RC4)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 0.50 \\ 2.00 & 1.00 \end{bmatrix}$	2.00	1 iterations, delta = 0.0E+0	0.0%
$\begin{bmatrix} \text{proximity to cities with over 250,000 inhabitants (RC5)} \\ \text{proximity to cities with 100,000 to 250,000 inhabitants (RC6)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 3.00 \\ 0.33 & 1.00 \end{bmatrix}$	2.00	1 iterations, delta = 0.0E+0	0.0%
<i>PV technology</i>				
$\begin{bmatrix} \text{proximity to road (RC3)} \\ \text{proximity to utility grid (RC4)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 3.00 \\ 0.33 & 1.00 \end{bmatrix}$	2.00	1 iterations, delta = 0.0E+0	0.0%
$\begin{bmatrix} \text{proximity to cities with over 250,000 inhabitants (RC5)} \\ \text{proximity to cities with 100,000 to 250,000 inhabitants (RC6)} \\ \text{proximity to mines (RC7)} \end{bmatrix}$	$\begin{bmatrix} 1.00 & 2.00 & 0.33 \\ 0.50 & 1.00 & 0.14 \\ 3.00 & 7.00 & 1.00 \end{bmatrix}$	3.003	2 iterations, delta = 7.1E-8	0.3%



**Table B.1**

List of interviews conducted by the first author during the summer of 2016.

Cluster	Institution / Company	Position of the interviewed representative	#
<b>Government</b>	Tanzania Electric Supply Company (TANESCO)	Principal Engineer	1
	Ministry of Energy and Minerals (MEM)	Energy Engineer	2
	Energy and Water Utilities Regulatory Authority (EWURA)	Principal Commercial Officer, Electricity	3
	Rural Energy Agency (REA)	Project Manager	4
	National Bureau of Statistics (NBS)	GIS Specialist	5
<b>Research</b>	University of Dar es Salaam (UDSM)	Deputy Vice-Chancellor for Research	6
		Senior Researcher and Assistant Lecturer	7
		Expert on Energy Systems	8
	The Tanzania Commission for Science and Technology (COSTECH)	Principal Research Officer	9
<b>Private Sector</b>	Ensol (T) Limited	Co-founder and Managing Director	10
	JUMEME Rural Power Supply Limited	Project Manager	11
	Energio Verda Africa Ltd.	Project Manager	12
	Hecate Energy (USA)	Development Associate	13
	NextGen Solar (USA)	Chief Executive Officer (CEO)	14
<b>Local NGOs</b>	Tanzania Renewable Energy Association (TAREA)	Chairman, Advisory Board	15
	Tanzania Traditional Energy Development Organization (TaTEDO)	Executive Director	16
<b>International NGOs</b>	ACRA	President of ACRA	17
	Freelancer (worked at Istituto Oikos Onlus)	Energy Consultant	18
<b>International Development Agencies</b>	The African Development Bank (AfDB)	Senior Energy Officer	19
	Embassy of Sweden, The Swedish International Development Cooperation Agency (Sida)	Programme Officer for Energy Development Cooperation Division (DCD)	20
	Delegation of the European Union to Tanzania and the East African Community	Programme Manager, Energy	21
	Embassy of USA, U.S. Agency for International Development (USAID)	Senior Energy Advisor	22
	International Finance Corporation (IFC), World Bank Group	Consultant and Programme Manager, Scaling up Renewable Energy Program (SREP)	23
	Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)	Technical Advisor on Renewable Energy	24
	UK Department for International Development (DFID)	Climate and Environment Adviser	25
	Tanzania's Energy & Minerals Development Partners Group Secretariat, UNDP	Former Coordinator	26
	United Nations Industrial Development Organization (UNIDO)	Coordinator, National Energy Projects	27

**Highlights:**

- Concentrated Solar Power (CSP) suitability map (5 categories) is proposed.
- Photovoltaics (PV) suitability map (5 categories) is proposed.
- Areas are calculated for each of the 5 categories of CSP and PV suitability maps.

## Data collection and preparation

## GIS-processing for excluding unsuitable areas

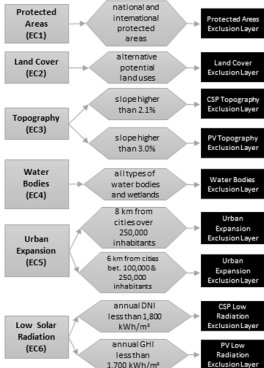
## Applying Multi-Criteria Decision-Making (MCDM) technique to rank suitable areas

**Study Area**  
(United Republic of Tanzania)

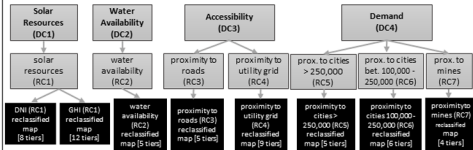
**Identifying Exclusion Criteria**

**Building the GIS Database**

### Conditions for exclusion



### Identifying Decision Clusters (DC) and Ranking Criteria (RC)



### Analytic Hierarchy Process (AHP)

Applying RC weights to respective layers and performing GIS-processing

Determining overall weights of RC

Pairwise comparison of DC and RC

Consistency check

CSP Exclusion Mask

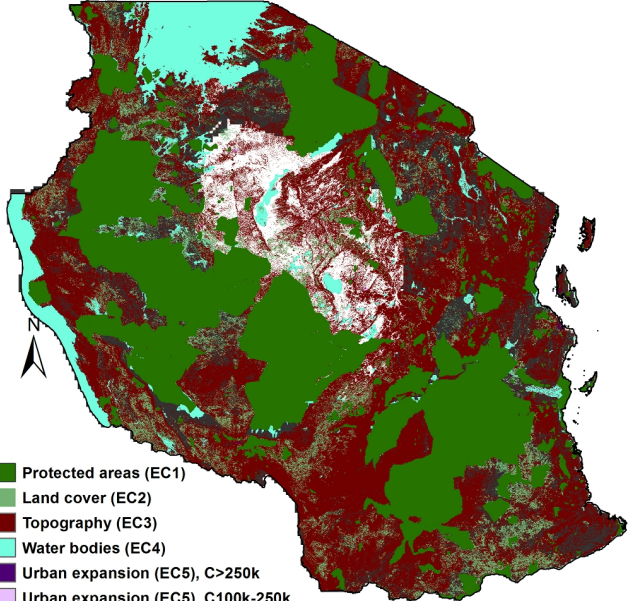
PV Exclusion Mask

Categorizing all available areas into 4 suitability categories:

- most suitable
- moderately suitable
- suitable
- least suitable

CSP suitability map (CSP hot spots)

PV suitability map (PV hot spots)



Protected areas (EC1)

Land cover (EC2)

Topography (EC3)

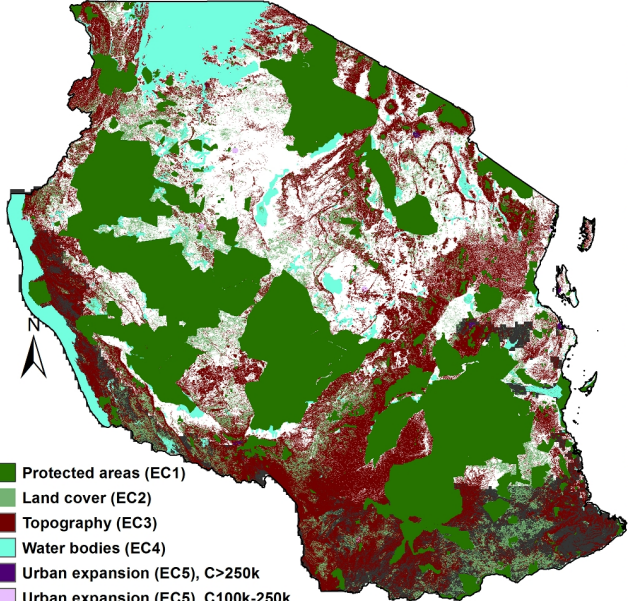
Water bodies (EC4)

Urban expansion (EC5), C>250k

Urban expansion (EC5), C100k-250k

Low solar radiation (EC6)

Available areas for CSP plants



Protected areas (EC1)

Land cover (EC2)

Topography (EC3)

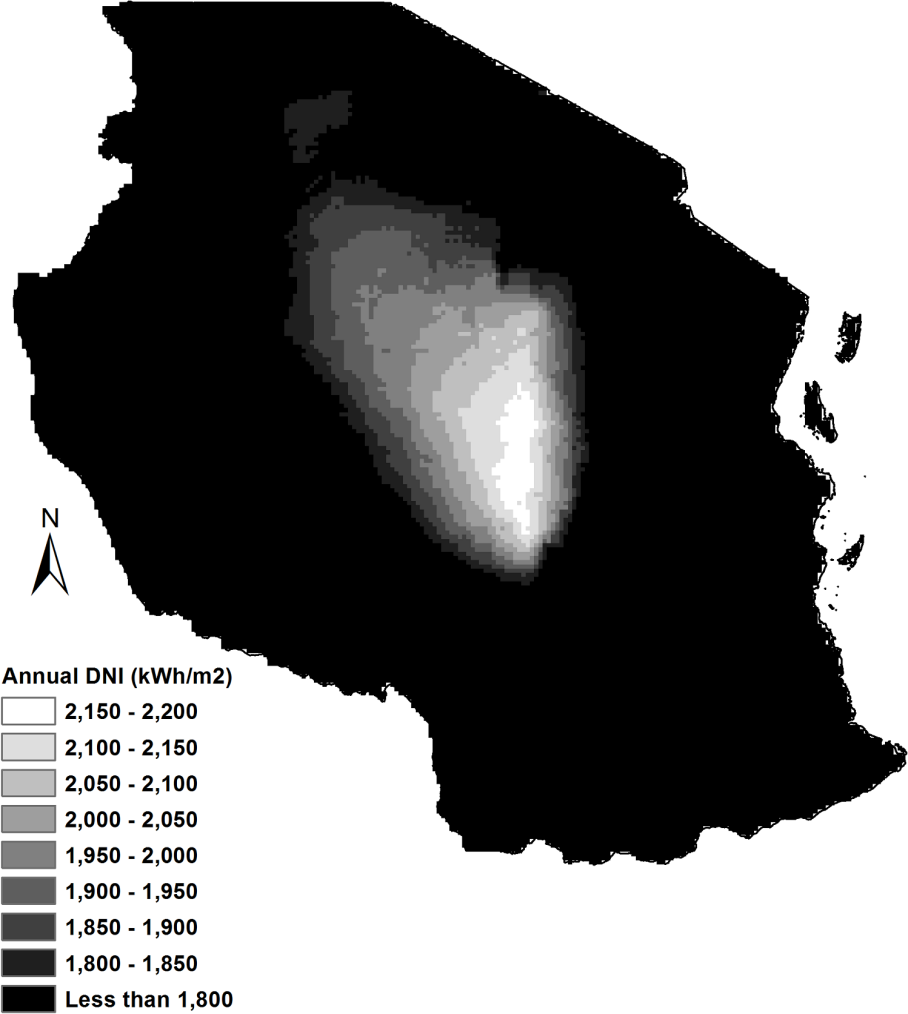
Water bodies (EC4)

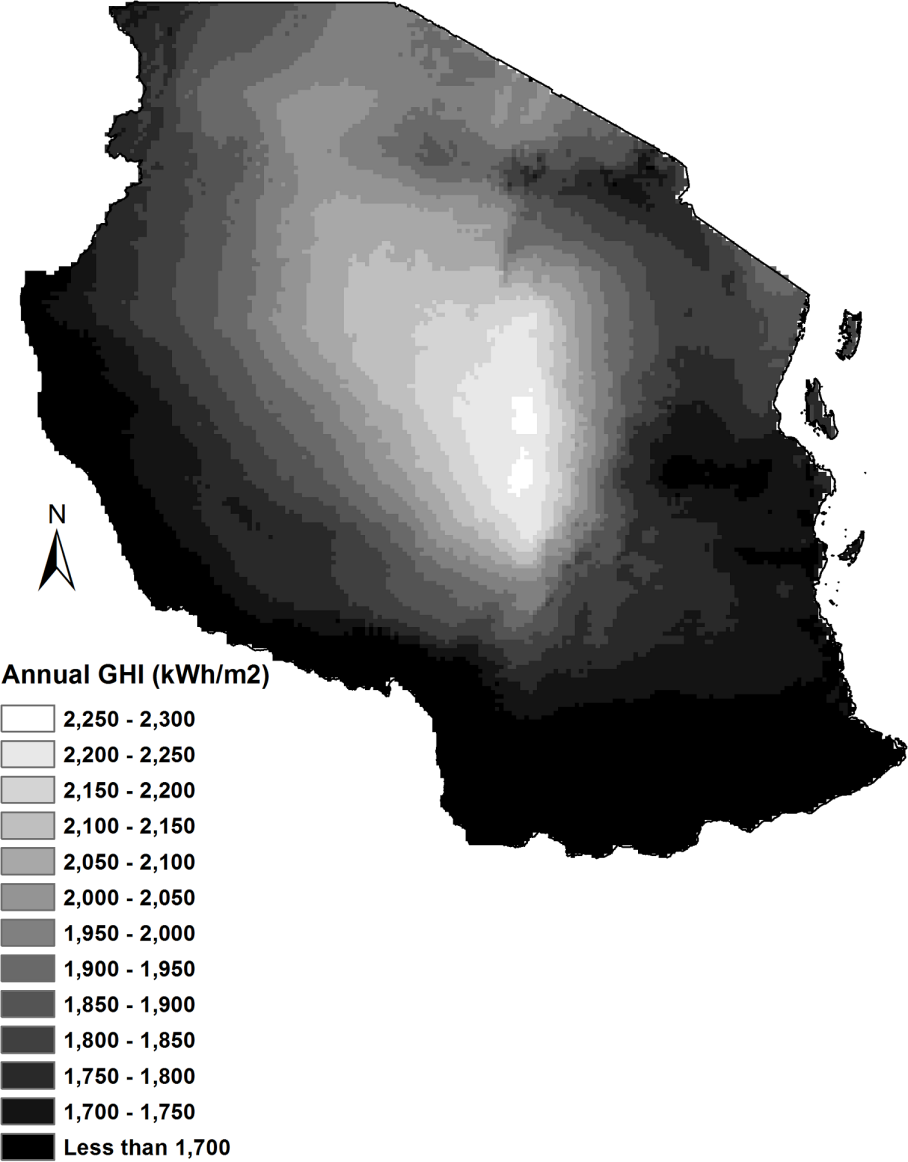
Urban expansion (EC5),  $C > 250k$

Urban expansion (EC5),  $C 100k-250k$

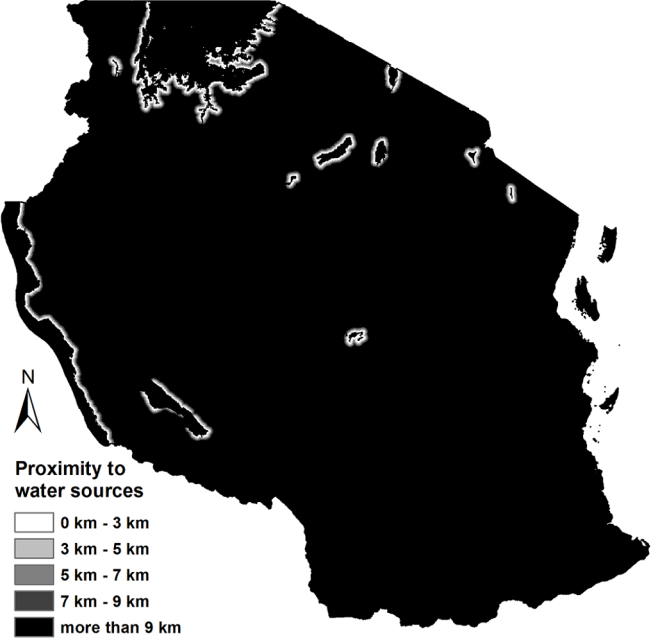
Low solar radiation (EC6)

Available areas for PV plants

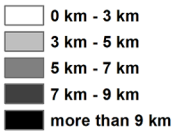


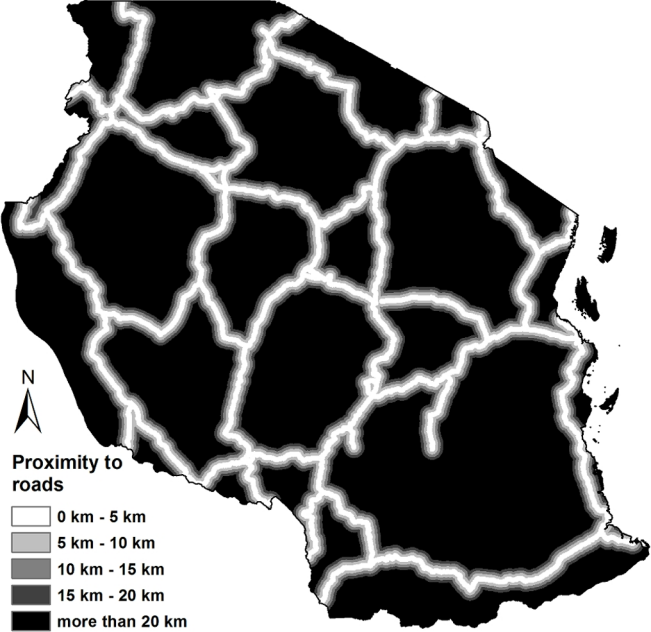


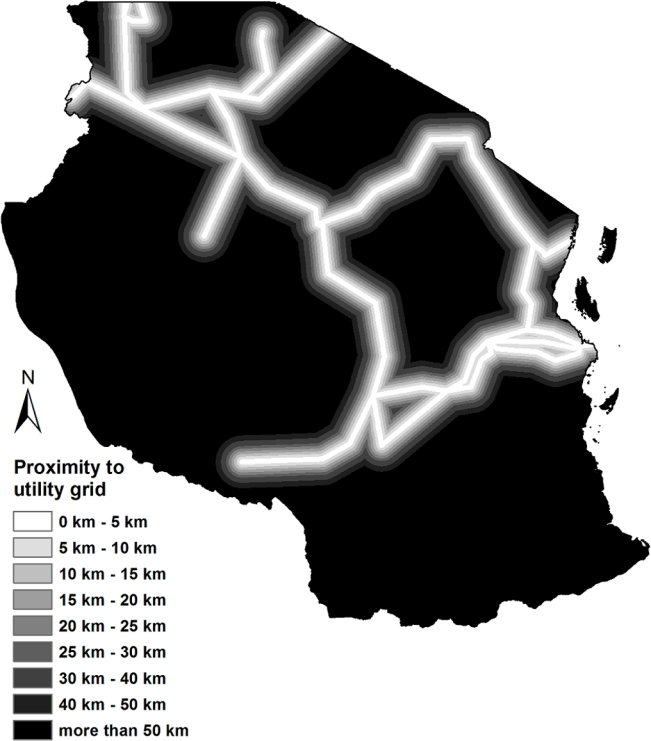


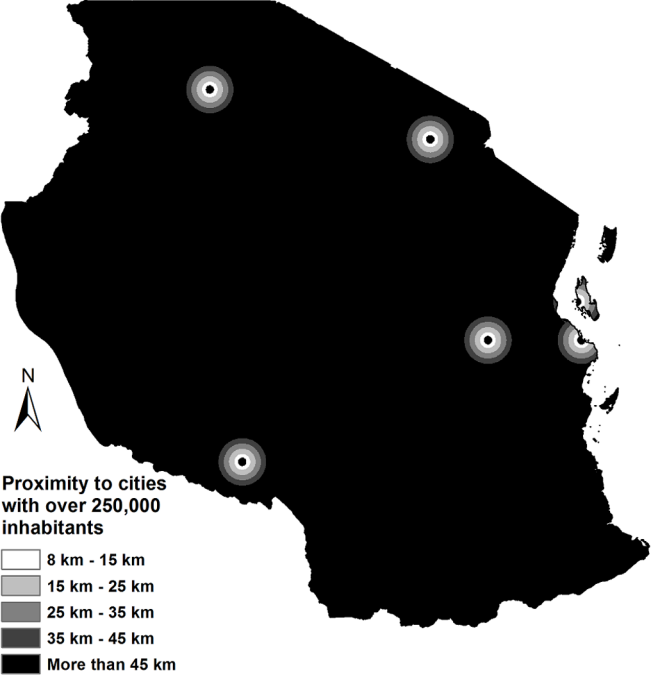


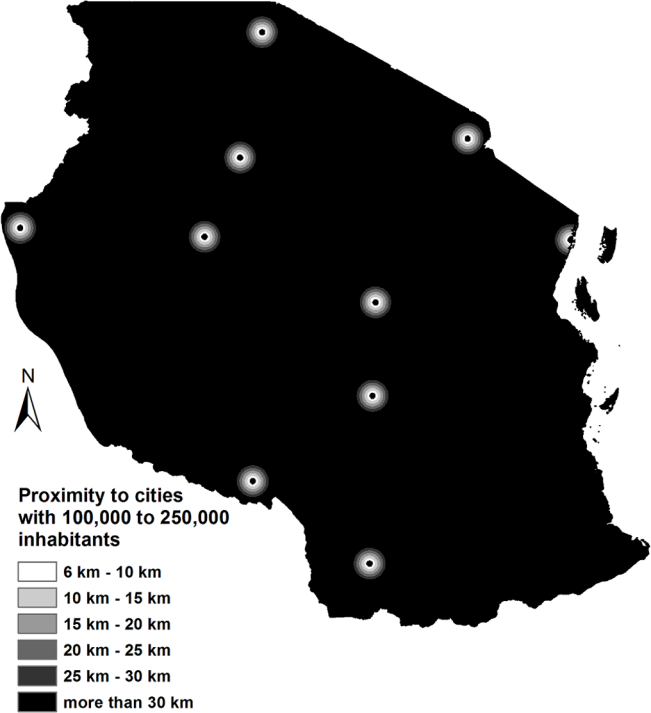
**Proximity to  
water sources**

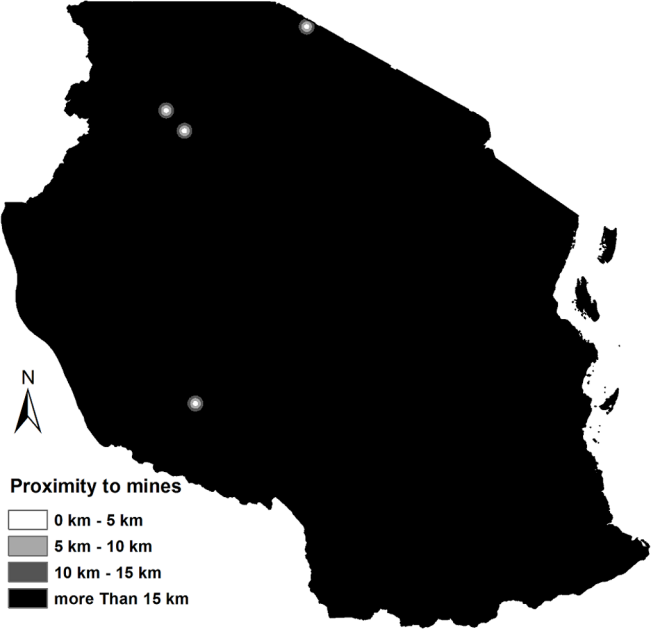


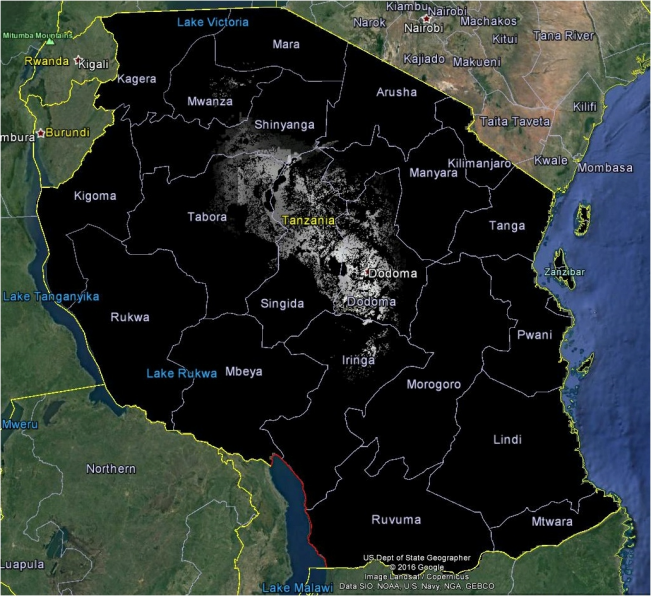


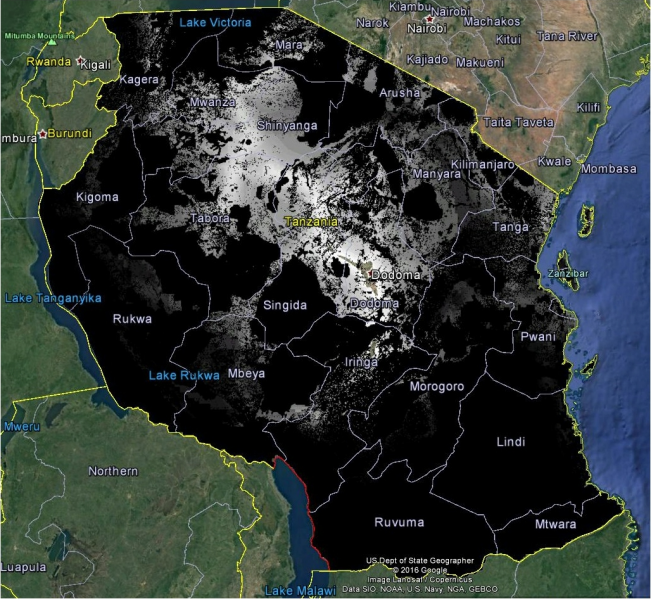












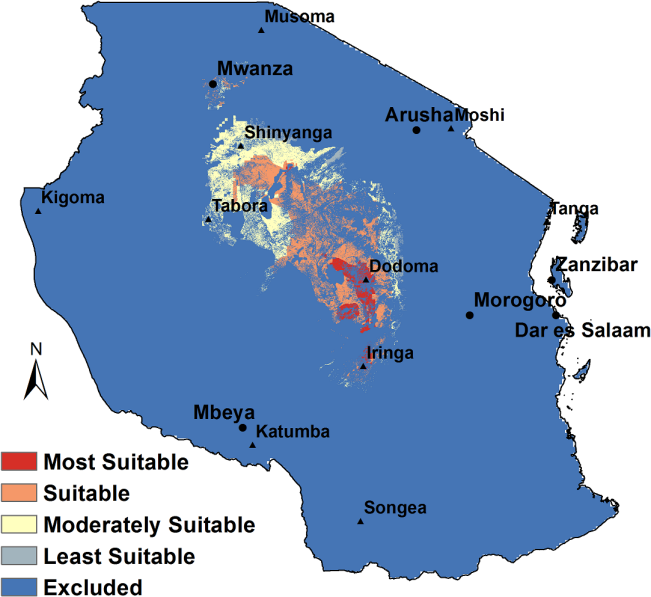
US Dept of State Geographer

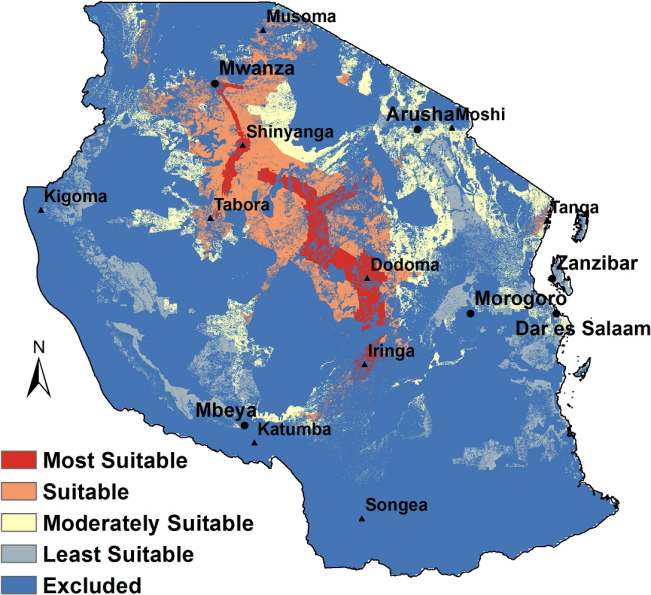
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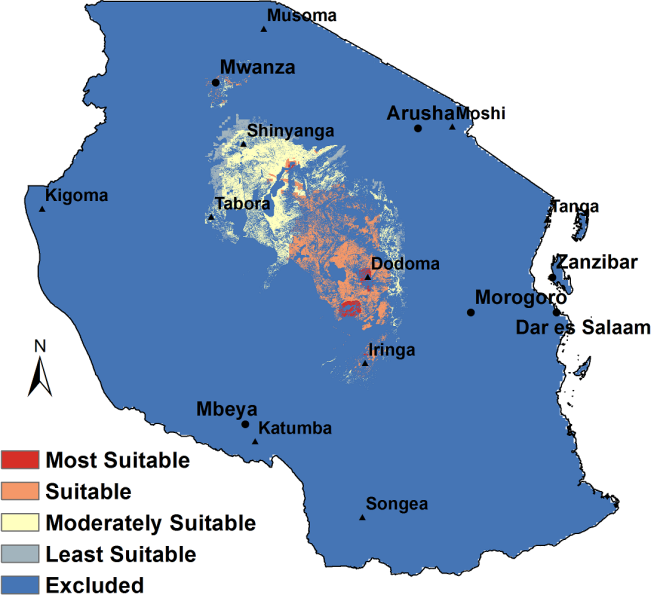
Image Landsat / Copernicus

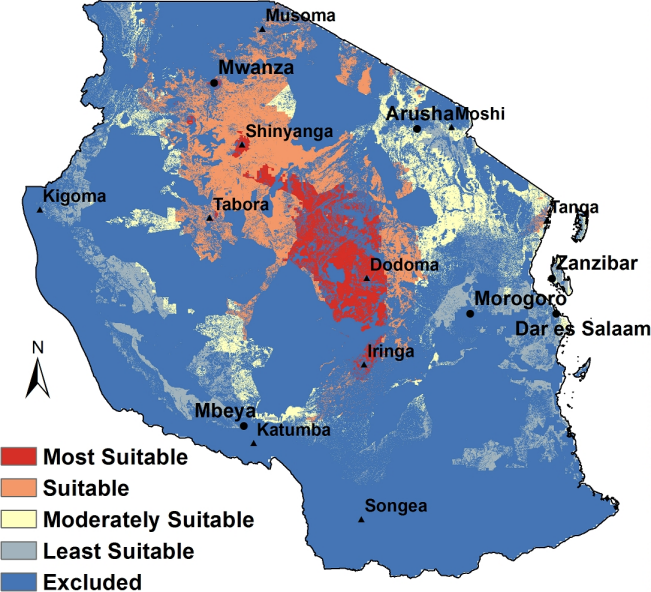
Data SIO NOAA U.S. Navy NGA GEBCO

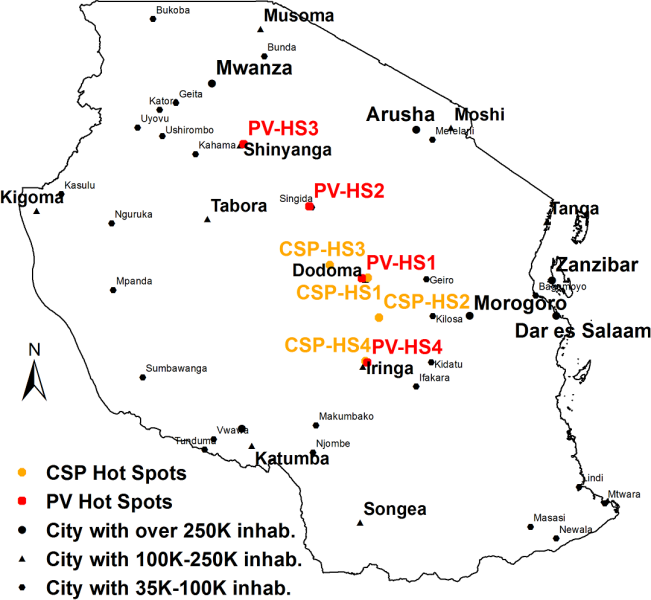












**Table 1**

Tiers of each ranking criterion

RC1 - Annual DNI			RC1 - Annual GHI		
Tier #	DNI (kWh/m <sup>2</sup> )	Value	Tier #	GHI (kWh/m <sup>2</sup> )	Value
1	2150-2200	100	1	2250-2300	100
2	2100-2150	95	2	2200-2250	95
3	2050-2100	90	3	2150-2200	90
4	2000-2050	85	4	2100-2150	85
5	1950-2000	80	5	2050-2100	80
6	1900-1950	75	6	2000-2050	75
7	1850-1900	50	7	1950-2000	70
8	1800-1850	40	8	1900-1950	65
			9	1850-1900	60
			10	1800-1850	40
			11	1750-1800	30
			12	1700-1750	20

RC2 - Proximity to water resources			RC3 - Proximity to roads			RC4 - Proximity to utility grid		
Tier #	Distance (km)	Value	Tier #	Distance (km)	Value	Tier #	Distance (km)	Value
1	0 - 3	100	1	0 - 5	100	1	0 - 5	100
2	3 - 5	80	2	5 - 10	80	2	5 - 10	90
3	5 - 7	70	3	10 - 15	60	3	10 - 15	80
4	7 - 9	60	4	15 - 20	40	4	15 - 20	70
5	more than 9 Km	0	5	more than 20 Km	0	5	20 - 25	60
						6	25 - 30	50
						7	30 - 40	40
						8	40 - 50	30
						9	more than 50 Km	0

RC5 - Proximity to cities with over 250,000 inhabitants			RC6 - Proximity to cities with 100,000 to 250,000 inhabitants			RC7 - Proximity to mines		
Tier #	Distance (km)	Value	Tier #	Distance (km)	Value	Tier #	Distance (km)	Value
1	8 - 15	100	1	6 - 10	100	1	0 - 5	100
2	15 - 25	70	2	10 - 15	80	2	5 - 10	80
3	25 - 35	60	3	15 - 20	70	3	10 - 15	40
4	35 - 45	40	4	20 - 25	50	4	more than 15 Km	0
5	more than 45 Km	0	5	25 - 30	40			
			6	more than 30 Km	0			

**Table 2**

AHP scale (using Saaty's discrete 9 value scale [48])

Intensity of weight	Definition	Explanation
1	Equal importance	Two criteria contribute equally to objectives
3	Weak/moderate importance	Experience and judgment slightly favoured one criteria over another
5	Essential or strong importance	Experience and judgment strongly favoured one criteria over another
7	Very strong or demonstrated importance	A criteria is favoured very strongly over another; its dominance demonstrated in practice
9	Absolute importance	The evidence favouring one criteria over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent scale values	Used to represent compromise between the priorities listed above
Reciprocals of above non-zero numbers		If criteria $i$ has one of the above non-zero numbers assigned to it when compared to criteria $j$ , then $j$ has the reciprocal value when compared with criteria $i$

**Table 3**

Decision clusters weights and ranking criteria overall weights

Decision Cluster (DC)	DC Weights (%)	Ranking Criteria (RC)	RC Overall Weights (%)
<i>CSP technology</i>			
<b>Solar Resources (DC1)</b>	<b>61.8</b>	solar resources (RC1)	<b>61.8</b>
<b>Water Availability (DC2)</b>	<b>20.3</b>	water availability (RC2)	<b>20.3</b>
<b>Accessibility (DC3)</b>	<b>13.4</b>	proximity to roads (RC3)	<b>4.5</b>
		proximity to utility grid (RC4)	<b>8.9</b>
<b>Demand (DC4)</b>	<b>4.5</b>	proximity to cities with over 250,000 inhabitants (RC5)	<b>3.4</b>
		proximity to cities with 100,000 to 250,000 inhabitants (RC6)	<b>1.1</b>
<i>PV technology</i>			
<b>Solar Resources (DC1)</b>	<b>69.6</b>	solar resources (RC1)	<b>69.6</b>
<b>Accessibility (DC3)</b>	<b>22.9</b>	proximity to roads (RC3)	<b>7.6</b>
		proximity to utility grid (RC4)	<b>15.3</b>
<b>Demand (DC4)</b>	<b>7.5</b>	proximity to cities with over 250,000 inhabitants (RC5)	<b>1.6</b>
		proximity to cities with 100,000 to 250,000 inhabitants (RC6)	<b>0.8</b>
		proximity to mines (RC7)	<b>5.1</b>



**Table 4**

Decision clusters weights and ranking criteria overall weights according to the Demand-driven Scenario

Decision Clusters (DC)	DC Weights (%)	Ranking Criteria (RC)	RC Overall Weights (%)
<i>CSP technology</i>			
<b>Solar Resources (DC1)</b>	<b>59.4</b>	solar resources (RC1)	<b>59.4</b>
<b>Water Availability (DC2)</b>	<b>21.2</b>	water availability (RC2)	<b>21.2</b>
<b>Accessibility (DC3)</b>	<b>4.9</b>	proximity to roads (RC3)	<b>1.6</b>
		proximity to utility grid (RC4)	<b>3.3</b>
<b>Demand (DC4)</b>	<b>14.5</b>	proximity to cities with over 250,000 inhabitants (RC5)	<b>10.9</b>
		proximity to cities with 100,000 to 250,000 inhabitants (RC6)	<b>3.6</b>
<i>PV technology</i>			
<b>Solar Resources (DC1)</b>	<b>69.6</b>	solar resources (RC1)	<b>69.6</b>
<b>Accessibility (DC3)</b>	<b>7.5</b>	proximity to roads (RC3)	<b>2.5</b>
		proximity to utility grid (RC4)	<b>5.0</b>
<b>Demand (DC4)</b>	<b>22.9</b>	proximity to cities with over 250,000 inhabitants (RC5)	<b>4.9</b>
		proximity to cities with 100,000 to 250,000 inhabitants (RC6)	<b>2.3</b>
		proximity to mines (RC7)	<b>15.6</b>